International Journal of Multidisciplinary Engineering in Current Research - IJMEC
Volume 8, Issue 9, September-2023, http://ijmec.com/, ISSN: 2456-4265

# USING ARTIFICIAL INTELLIGENCE WHAT CAUSES SENTIMENTAL ANALYSIS ON SOCIAL MEDIA.

Rahma Bamasdoos[1], Dr. Mohd.Abdul Bari[2] , Dr..L.K Suresh Kumar[3]
[1]PG Scholar, Department of CSE, ISL Engineering College
[2]Professor & HOD CSE, ISL Engineering College
[3]BOS & Associate Professor ;Department of Computer Science ;UCE, Osmania University

**Abstract:** With the use of sentiment analysis software, business leaders can keep tabs on public opinion as it relates to certain brands, topics, and events. Millions of people utilize services like Twitter to share their thoughts on a wide range of issues, and these technologies give dashboards to monitor the good, negative, and neutral views expressed there. However, these techniques do not yet automatically extract explanations for differences in sentiment, which makes it challenging for decision-makers to infer appropriate actions. In this research, we begin by selecting the best performer among many Sentiment Analysis classifiers for brief texts by comparing their performance. Then, we provide the Filtered-LDA framework, which much outperforms prior techniques for deducing Twitter users' emotions. To identify potential explanations for shifts in opinion, the system employs cascaded LDA Models with adjustable hyperparameters. Finally, a Topic Model with a high Coherence Score is used to extract human-understandable Emerging themes by filtering out tweets on old themes. At last, a unique Twitter dashboard for emotion reasoning is shown, which compiles the most representative tweets for each potential explanation and displays them in a single place. The categorization procedure would make use of machine learning and deep learning techniques. Sentiment may be tracked or analyzed with the use of social media. This study provides a summary of the ways in which artificial intelligence has been used to sentiment analysis on social media data to identify nervousness and hopelessness.

## INTRODUCTION

Hundreds of millions of tweets are being posted every day to discuss various topics [1] like politics, products, news, celebrities, etc. This rich source of users' feedbacks makes it essential for many decision-makers to persistently monitor Twitter and other social media platforms. Luckily, there are many software applications that can handle this task as illustrated in Table 1 examples. Such tools can monitor sentiment changes and spikes about specific targets, however, so far, none of the available tools has taken a step ahead by extracting possible reasons behind these sentiment variations.

**TABLE 1** Some Sentiment Analysis Software Applications [2]

| Name | Live Text | Free Plan | Illustration |
|---|---|---|---|
| MonkeyLearn | No | Yes | No |
| IBM Watson | Yes | Yes | No |
| Lexalytics | Yes | No | Yes |

| | | | |
|---|---|---|---|
| MeaningCloud | Yes | Yes | No |
| Rosette | Yes | No | No |
| Repustate | Yes | Yes | No |
| Clarabridge | No | No | No |
| Aylien | Yes | No | No |

In the context of social media, however, the use of sentiment analysis—a kind of analytics that detects whether a person's words and phrases are positive or negative—can be crucial. Noting that over the next six years, a new kind of AI automation technology software known as natural language processing will replace most of what content writers are doing at the moment. Machines are replacing people in the workforce, and they will soon be able to do these tasks at a higher quality and rate than humans can because to advancements in AI. And if that weren't enough, recent studies have shown that combining AI with NLP would improve recognition and familiarity in information delivery systems. Everything is following a natural progression toward this future technology. Sentiment analysis in the context of social media is...

A piece of writing's tone may be determined with the use of a method called sentiment analysis. It may be used to assess the overall tone of a piece of writing.Several different fields may benefit from sentiment analysis. It can help with things like figuring out which advertising campaigns have the best shot of succeeding. A person's level of happiness, sadness, or anger may also be gauged using this method.

To accomplish several goals, sentiment analysis is an effective social media monitoring technique. Confidence, stress, expectations, etc., are only a few. Typically, a company's Business Intelligence division will do sentiment analysis with assistance from the Digital Marketing division.

***One way to learn how customers feel about a service or brand is via social media sentiment research.***

Sentiment research is essential if you want to discover how customers feel about your company. In particular, understanding your consumers' social media interactions using sentiment analysis might help you better serve them. As a subset of social listening, sentiment analysis is worth considering. Sentiment analysis delves into the positive, negative, and neutral feelings around mentions of brands and companies.

What's the Big Deal About Sentiment Analysis?

You may receive a qualitative reading of every single mention and discussion on social media with the help of sentiment analysis. The opinions of your customers are revealed in every discussion that mentions your brand, and these opinions may inform your business decisions. Sentiment analysis refers to a set of procedures and methods that reveal customer feedback on a service or product. Sentiment analysis is an automated method that uses Natural Language Processing (NLP) technologies to analyze the sentiments (e.g., attitudes, emotions, ideas, views, etc.) expressed in written or spoken language. Some users have turned to existing Topic Visualization techniques to monitor the development of topics and visually link Topics Over Time curves with sentiment trends in the absence of dedicated Sentiment Reasoning software solutions. To provide only one example, Yin et al. [3] sought to decipher shifts in Twitter user attitude towards Covid-19. By using Dynamic Topic Model (DTM) [4] to track the development of themes over time, they were able to manually connect certain subjects to shifts in sentiment in tweets about Covid-19. There are more than 8 million tweets in the dataset under study, making it difficult to independently evaluate the reasons drawn from it, since they depend on the reliability of a manually chosen subset of subjects determined by the Coherence Scores of DTM. Even the greatest Coherence Scores will not ensure precise topical analysis later on, as we will demonstrate. Researchers have taken on the difficult task of deciphering public opinion and tracking its shifts throughout time. Nonetheless, Poria et al. [5] foresaw Sentiment Reasoning as one of the primary developments in the area of Sentiment Analysis. In this study, we investigate the challenge of automating the identification of causes for observed shifts in online opinion.

### A. Existing Sentiment Reasoning Methods

There are two issues that feeling Reason Mining attempts to address: determining the motivation behind a feeling and making sense of emotional shifts. Many techniques, such as Aspect-Based approaches, Supervised Learning, Topic Modeling, and Data Visualization [8], were developed to solve the first issue. Although this area of study has seen significant advancement, very few scholars have taken on the second issue. There were primarily three ways that sentiment variations were interpreted. One of them is monitoring emotional outbursts, another is latent Dirichlet allocation in the foreground and background, and a third is identifying events. We provide a short overview of these methods and highlight their primary drawbacks, which were previously discussed in [8].

#### 1) Tracking Sentiment Spikes

Giachanou and Crestani [9] used the SentiStrength [10] instrument to track the average tone of tweets; they then utilized an outlier identification technique to locate instances of unusually positive or negative sentiment. The next step is to use LDA on the spike's tweets to find the most frequently mentioned topics, as it is likely that they are the driving force behind the uptick in negative sentiment. Although this method may be useful in determining the causes of sentiment shifts in certain circumstances, it is based on the incorrect premise that large shifts in sentiment invariably lead to an increase in mood in general [8]. In addition, LDA's precision is essential to this approach since it allows us to monitor how TOTs change over time. As shown in Fig. 1, we used LDA to a SIGIR dataset consisting of 924 abstracts on Information Retrieval topics spanning the years 2000-2012. We found that K = 17 was the optimal number of topics for the dataset, and that this number gave the Topic Model its greatest coherence score possible after we manually categorized the topics. Both "Feature Space Hashing" and "Social Network Twitter" should not have been emerging as research trends before 2010, but LDA did not account for this. Even though the Twitter platform didn't exist until a few years later, the LDA trend demonstrates that Twitter was a hot issue in 2003. Because of this, low-frequency new topics were merged with old subjects in LDA output when using the Tracking Sentiment Spikes approach.

International Journal of Multidisciplinary Engineering in Current Research - IJMEC
Volume 8, Issue 9, September-2023, http://ijmec.com/, ISSN: 2456-4265

*2) FB-LDA*

By manually analyzing real-world tweets about specific targets, Tan et al. [6] constructed the FB-LDA Model and found that the primary causes of sentiment changes are causally connected to Emerging Topics. When the aggregated ratio of positive to negative sentiment changes by more than 50 percent, they determined that this was the beginning of the Foreground phase. Next, they used the FB-LDA model, which first pulls out all Foreground Topics and then examines documents from the earlier Background time period. The model first determines the degree of similarity between Foreground and Background subjects, and then it extracts all Emerging subjects, or Foreground topics that do not share a high degree of similarity with Background topics.

In Fig. 2, discovered Emerging Topics are colored green to make the Foreground-Background topic classification process more straightforward. At the end, we use a Least-Disciplined-Average (RCB-LDA) model to find the one tweet that best encapsulates each emerging theme.

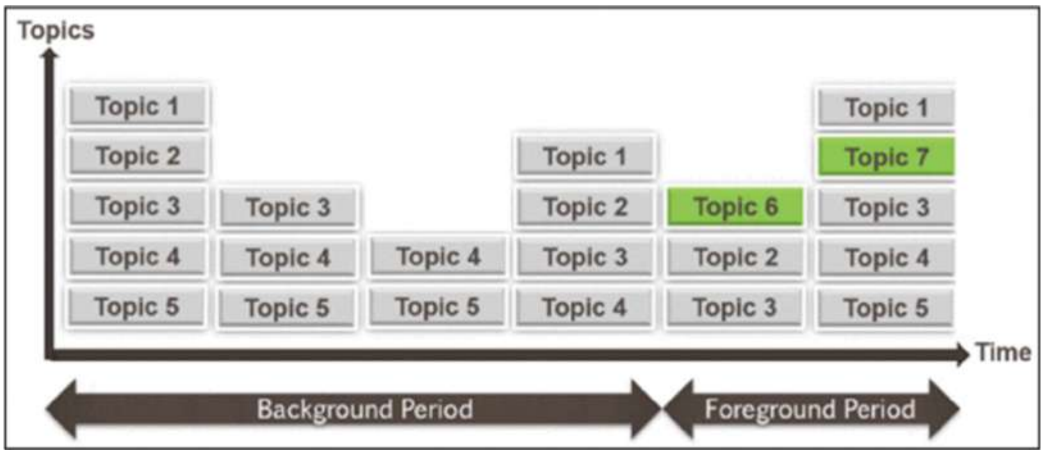



*Figure 2: Emerging Topics Appear Only In Foreground Documents.*

*3) Event Detection*

Jiang et al. [11], motivated by the Topic-Sentiment Mixture (TSM) models [12] to analyze sentiment shifts, developed a custom Event Detection approach for evaluating shifts in sentiment by tracking sudden spikes in the number of documents for discussed subjects and correlating them with shifts in sentiment. Topic Sentiment Alteration Analysis (TSCA) is the name of their methodology. Both probabilistic latent semantic analysis (PLSA) [13] and a rule-based approach to sentiment extraction are used. While Event Detection performed well when highly discussed inside documents, it failed to identify less often discussed themes, which may be the primary drivers of sentiment differences. [8].

**B. Sentiment Analysis for Short Texts**

Sentiment analysis, which seeks to identify the subjectivity and polarity of texts at the sentence-, document-, and aspect-levels [14], has seen a proliferation of methods over the last four decades. Research on Sentiment Analysis blossomed in the 1980s, with studies examining topics including the cognitive features of emotions and the construction of emotional lexicons. WordNet [18], POS Tagging [19], Parsing Trees based on Statistical

ISSN: 2456-4265

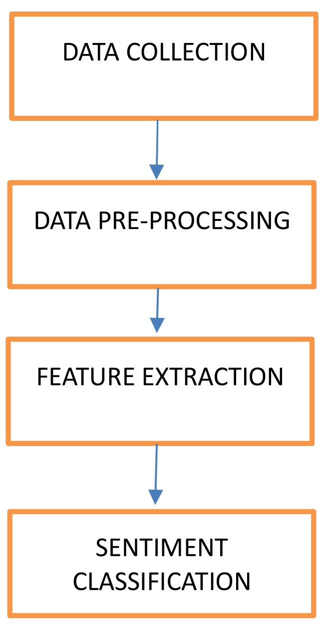

DOI: https://doi-ds.org/doilink/09.2023-61724673

Methods [20], [21], predicting the semantic orientation of adjectives [22], and Fuzzy Model [23, 24] were all introduced in the 1990s for use in data mining and sentiment analysis.

Major advancements in Sentiment Analysis research were made towards the turn of the new millennium. SentiWordNet [25] was released to fill the need for a Sentiment Analysis-specific version of WordNet, and Sentic Computing [26] was employed to take Sentiment Analysis to the next level. The topic of Sentiment Analysis has recently been dominated by Machine Learning methods. Supervised Learning methods were used in the vast majority of these investigations [27], [28], although it was shown that Unsupervised Learning methods [29] might also provide promising outcomes. For languages with sparse vocabularies, the bootstrapping approach was proposed to construct a lexicon of sentiments/subjectivity [30]. Some researchers also employed and saw success with Semi-Supervised Learning [31] and Hybrid [32] approaches.

When compared to other Machine Learning methods for Sentiment Analysis [33], Deep Learning techniques, such as Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), and Deep Neural Networks (DNN), have shown excellent results, particularly when Word Embedding [34] representation is used with the Deep Learning algorithms. Another Neural Network-based method that has proven effective for Sentiment Analysis is the Bidirectional Encoder Representations from Transformers (BERT) algorithm [35]. The most common methods for dealing with Sentiment Analysis are shown in Fig. 3.

Sentiment analysis is a method for determining the overall tone of a piece of text and categorizing it as positive, negative, or neutral. The primary focus will be on analyzing consumer behavior in a manner that benefits corporate growth. It's a visual representation of not just positive, negative, and neutral polarity, but also a wide range of human emotions. Several NLP (Natural Language Processing) methods are used. Word context mining reveals how consumers feel about a company. It also helps in establishing whether or not the product a company is producing will sell well in the marketplace.







DOI: https://doi-ds.org/doilink/09.2023-61724673

International Journal of Multidisciplinary Engineering in Current Research - IJMEC
Volume 8, Issue 9, September-2023, http://ijmec.com/, ISSN: 2456-4265

With the emergence of social media, additional challenges faced the Sentiment Analysis task as handling short texts requires special considerations. For instance, extracting sentiment from tweets through Supervised Learning methods would need significantly large annotated multi-domain datasets. As a result, Lexicon-based methods were found more efficient, so far, for handling short texts' Sentiment Analysis [36]. Three Lexicon-based tools are still being used frequently by various researchers to extract sentiment from short texts. These are SentiStrength [37], TextBlob [38], and VADER [39].

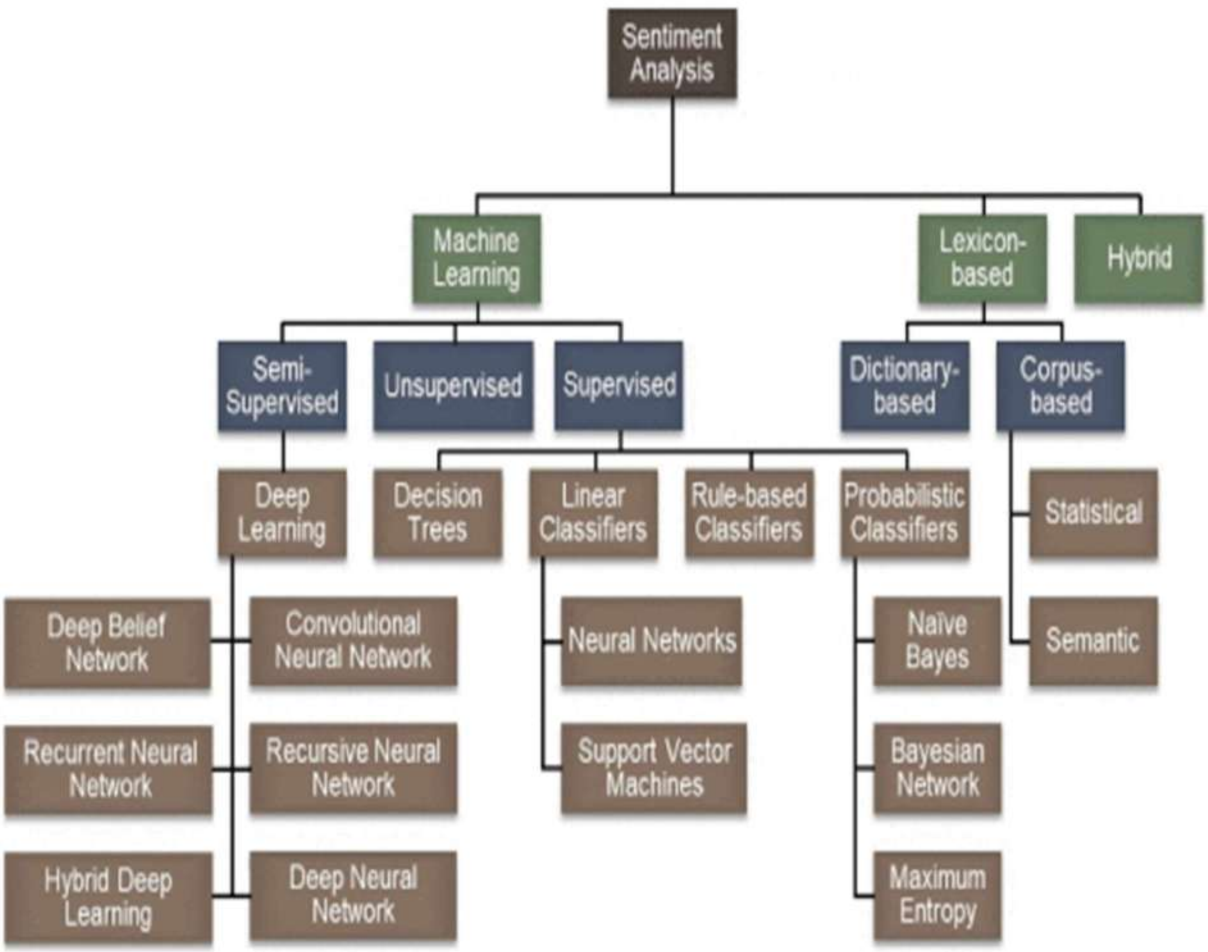



*Figure 3: Main Sentiment Analysis Techniques.*

**Analysis of Social Networks**

When referring to individuals, groups, organizations, computers, and other interconnected information entities, the term "social network analysis" denotes the process of finding and realizing the connections and data flow between these entities. In a social network, the individuals and organizations make up the nodes, and the connections between them are represented by the links. Analyses, such as graphical and numeric dissections of interpersonal connections, are carried out. Researchers use the idea of degrees to gauge a node's level of network activity, or the sum of its direct connections.

One or more nodes that serve as hubs are what define a centralized network. If the network rapidly divides into disconnected sub-networks, vital nodes are either damaged or deleted. It has the potential to become a bottleneck. If a key component of a centralized system is removed or rendered inoperable, the whole system might collapse. Hubs are very central nodes in a network.

**Strategies for Artificial Intelligence**

Artificial intelligence (AI) refers to the study and creation of computer systems with the ability to mimic human intellect in areas such as perception, voice recognition, decision making, and language translation. Several Deep Learning and Machine Learning Methods are discussed here.

**Approaches to Machine Learning**

Machine Learning refers to the process wherein a machine is taught to make correct predictions [24, 27, 29] by being fed data. It demonstrates how an algorithm [2, 16] that improves its predictions with experience works. Machine learning relies on four primary methods: supervised, unsupervised, semi-supervised, and reinforcement learning. Machine learning methods are compared in Table 1.

**Comparing Sentiment Analysis Classifiers**

Specifically, we (1) compare the accuracy of main classifiers on the US Airlines Twitter Dataset, and (2) test their consistency when the domains of training dataset and testing dataset are different using the Ground Truth dataset, all with the goal of selecting the best performing Sentiment Analysis classifier for our Twitter dataset.

NLTK, Spacy, Pandas, Numpy, Sklearn, Genism, Matplotlib, Torch, Transformers, Keras, Tensorflow, Sentistrength, TextBlob, and VaderSentiment were only some of the packages, wrappers, and libraries that we utilized in Python 3.9 for text preprocessing and Sentiment Analysis categorization. Deep Learning methods benefit from the word2vec format to improve their classification accuracy [33]. Word embeddings are learned with the help of a 2-layer Neural Network [34]. Since negation keywords are crucial for determining the polarity of a feeling, they are not removed from the text during the preprocessing step. VADER is able to give sentiment levels to both Emoticons and words, so they are both retained after application. Emoticons have their Wikipedia definitions substituted automatically by other sentiment classifiers [47]. On the US Airlines Dataset, the acquired accuracy for each classifier is shown in Fig. 6. Ninety percent of the tweets were utilized for training Learning-based algorithms, while ten percent were used for testing. The same image depicts the outcomes of applying Deep Learning algorithms to the US Airlines Dataset using the Word2vec format, as described in [33].




DOI: https://doi-ds.org/doilink/09.2023-61724673

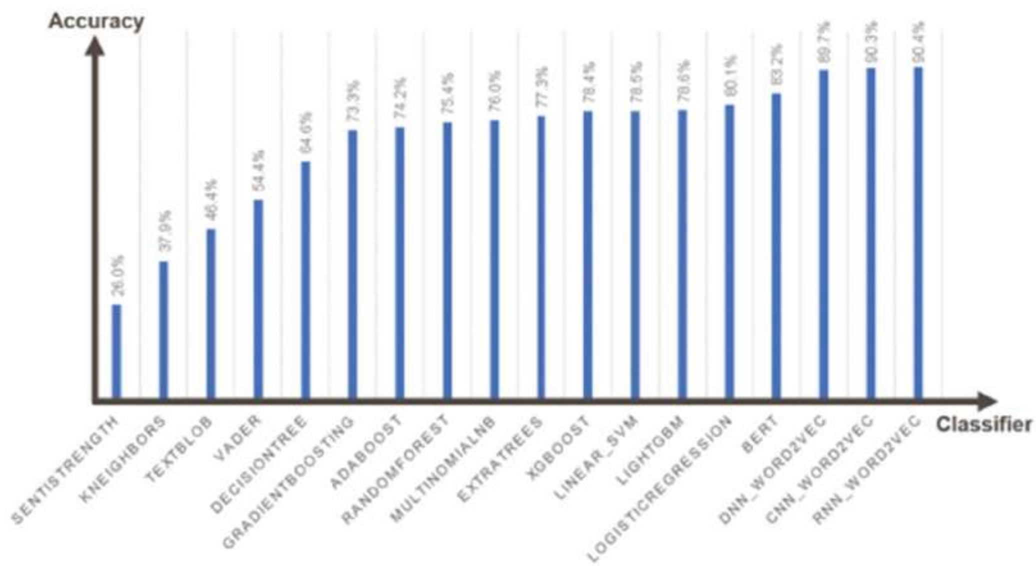



*Figure 6: Accuracy Of Sentiment Classifiers Trained And Tested On Same Twitter Domain.*

As can be seen in Fig. 7, re-testing on the Ground Truth Twitter dataset yielded wildly varying results for each Learning-based approach, with VADER providing the best accuracy, followed by TextBlob. Learning-based algorithms cannot achieve high classification accuracy when trained on a small single-domain Twitter dataset and evaluated on a different domain since there is currently no big Twitter dataset containing annotated positive, negative, and neutral attitudes.

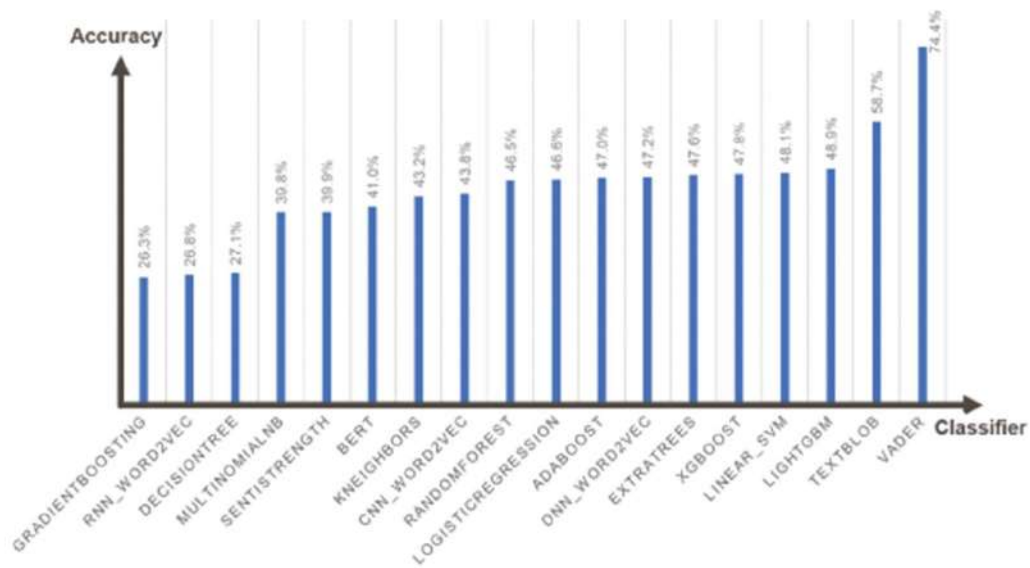



*FIGURE 7: Accuracy of sentiment classifiers trained on one domain and tested on a different twitter domain.*

We found that several of the Learning-based algorithms performed well when trained and evaluated on the same domain as US Airways' customer reviews. When evaluated on the Apple goods domain, however, the same


DOI: https://doi-ds.org/doilink/09.2023-61724673

trained models did not perform well. For the Stanford Twitter Dataset (STD-2009), the results from VADER and TextBlob Lexicon-based approaches are more trustworthy.

VADER was shown to be the most accurate Lexicon-based sentiment classifier when compared to TextBlob, SentiWordNet, and AFINN on Twitter by Botchway et al. [48].

VADER (Valence Aware Dictionary for sEntiment Reasoning) was created to tackle problems with sentiment categorization for social media messages, as described in [39]. It combines elements of both Rule-based and Lexicon-based systems. VADER can recognize slang, acronyms, and other forms of jargon. It also takes into consideration basic linguistic patterns seen on Twitter, such as negation, punctuation, obfuscation, and hyperbole.

VADER's efficiency is well-suited for real-time Twitter processing since its straightforward technique requires less computing resources. It also doesn't need training, unlike Learning-based algorithms, therefore it's performance isn't drastically altered by the changes between training and testing datasets. Accordingly, we will use VADER in our Filtered-LDA Sentiment Reasoning tests.

## Conclusion:

Interpretation of feelings/opinions Since sentiments are used to evaluate human behavior, mining comprehends the emotions, replicas, and judgments derived from texts or other data used in data analysis or mining, web mining, and sociable media analytics. You may classify them as either beneficial or harmful, or even neutral. It finds viewpoints, communicates their stance, and places them in appropriate division-smart categories. The information gathered through reading their minds, selecting relevant details, relegating emotional content, and finally quantifying the sentiment polarity. It's great for discussing people's thoughts on products in the business world, the state of the stock market, the mindset of news consumers, and the outcome of political disputes. Emotions may be pushed to the background in several ways. Learning in the context of Machine Learning may be broken down into two categories: supervised and unsupervised. Learning from unlabeled to identify the supplied input data is known as unsupervised learning, whereas supervised learning involves the creation of a model using learnt data and the prediction of the target class for the specific data. To integrate knowledge about several levels of feature description via procedures and behaviors, "deep understanding" is a crucial subfield in Machine Learning.

## 1. References:

1. P. Tighe, R. Goldsmith, M. Gravenstein, H. Bernard and R. Fillingim, "The painful tweet: Text sentiment and community structure analyses of tweets pertaining to pain", *J. Med. Internet Res.*, vol. 17, no. 4, pp. 1-19, 2015.

2. K. Shakhovska, N. Shakhovska and P. Vesely, "The sentiment analysis model of services Providers' feedback", *Electron. J.*, vol. 9, no. 11, pp. 1-15, 2020.
3. H. Yin, S. Yang and J. Li, "Detecting topic and sentiment dynamics due to COVID-19 pandemic using social media", *Proc. Int. Conf. Adv. Data Mining Appl. (ADMA)*, 2020.
4. D. M. Blei and J. D. Lafferty, "Dynamic topic models", *Proc. 23rd Int. Conf. Mach. Learn. (ICML)*, 2006.
5. S. Poria, D. Hazarika, N. Majumder and R. Mihalcea, "Beneath the tip of the iceberg: Current challenges and new directions in sentiment analysis research", *IEEE Trans. Affect. Comput.*, Nov. 2020.
6. S. Tan, Y. Li, H. Sun, Z. Guan, X. Yan, J. Bu, et al., "Interpreting the public sentiment variations on Twitter", *IEEE Trans. Knowl. Data Eng.*, vol. 26, no. 5, pp. 1158-1170, May 2014.
7. A. Goldstone, S. Galán, C. L. Lovin, A. Mazzaschi and L. Whitmore, "An interactive topic model of signs", *Signs J.*, 2014.
8. F. Alattar and K. Shaalan, "A survey on opinion reason mining and interpreting sentiment variations", *IEEE Access*, vol. 9, pp. 9636-9655, 2021.
9. Hafsa Fatima, Shayesta Nazneen, Maryam Banu, Dr. Mohammed Abdul Bar," Tensorflow-Based Automatic Personality Recognition Used in Asynchronous Video Interviews", Journal of Engineering Science (JES), ISSN NO:0377-9254, Vol 13, Issue 05, MAY/2022
10. Mohammed Shoeb, Mohammed Akram Ali, Mohammed Shadeel, Dr. Mohammed Abdul Bari, "Self-Driving Car: Using Opencv2 and Machine Learning", The International journal of analytical and experimental modal analysis (IJAEMA), ISSN NO: 0886-9367, Volume XIV, Issue V, May/2022
11. Mr. Pathan Ahmed Khan, Dr. M.A Bari,: Impact Of Emergence With Robotics At Educational Institution And Emerging Challenges", International Journal of Multidisciplinary Engineering in Current Research(IJMEC), ISSN: 2456-4265, Volume 6, Issue 12, December 2021,Page 43-46
12. A. Giachanou, I. Mele and F. Crestani, "Explaining sentiment spikes in Twitter", *Proc. 25th ACM Int. Conf. Inf. Knowl. Manage. (CIKM)*, Oct. 2016.
13. E. Guzman and W. Maalej, "How do users like this feature? A fine grained sentiment analysis of app reviews", *Proc. IEEE 22nd Int. Requirements Eng. Conf. (RE)*, Aug. 2014.
14. Y. Jiang, W. Meng and C. Yu, "Topic sentiment change analysis", *Proc. Int. Workshop Mach. Learn. Data Mining Pattern Recognit. (MLDM)*, 2011.
15. Q. Mei, X. Ling, M. Wondra, H. Su and C. X. Zhai, "Topic sentiment mixture: Modeling facets and opinions in Weblogs", *Proc. 16th Int. Conf. World Wide Web*, 2007.
16. T. Hofmann, "Probabilistic latent semantic analysis", *Proc. 22nd Annu. Int. ACM SIGIR Conf. Res. Develop. Inf. Retr. (SIGIR)*, 1999.
17. B. Pang and L. Lee, "Opinion mining and sentiment analysis", *Found. Trends Inf. Retr.*, vol. 2, no. 1, pp. 1-135, 2008.
18. A. Banfield, Unspeakable Sentences: Narration and Representation in the Language of Fiction, New York, NY, USA:Law Book Co of Australasia, 1982.

19. Mohammed Nadeem Shareef, Junaid Hussain, Mohammed Khaja Adnan Ali Khan,, Dr. Mohammed Abdul Bari .” Crypto Jacking”, Mathematical Statistician and Engineering Applications, ISSN: 2094-0343, 2326-9865, Vol 72 No. 1 (2023), Page Number: 1581 – 1586
20. Mohammed Fahad, Asma Akbar, Saniya Fathima, Dr. Mohammed Abdul Bari ,” Windows Based AI-Voice Assistant System using GTTS”, Mathematical Statistician and Engineering Applications, ISSN: 2094-0343, 2326-9865, Vol 72 No. 1 (2023), Page Number: 1572 - 1580
21. Syed Shehriyar Ali, Mohammed Sarfaraz Shaikh, Syed Safi Uddin, Dr. Mohammed Abdul Bari, “Saas Product Comparison and Reviews Using Nlp”, Journal of Engineering Science (JES), ISSN NO:0377-9254, Vol 13, Issue 05, MAY/2022
22. T. Winograd, Language As a Cognitive Process: Syntax, Lansing, MI, USA:Addison Wesley, vol. 1, 1983.
23. G. Clore, A. Ortony and M. Foss, "The psychological foundations of the affective lexicon", *J. Personality Social Psychol.*, vol. 53, no. 4, pp. 751-766, 1987.
24. G. A. Miller, R. Beckwith, C. Fellbaum, D. Gross and K. J. Miller, "Introduction to WordNet: An on-line lexical database", *Int. J. Lexicogr.*, vol. 3, no. 4, pp. 235-244, 1990.
25. E. Brill, "Some advances in transformation-based part of speech tagging", *Proc. 12th Nat. Conf. Artif. Intell. (AAAI)*, 1994.
26. Mohammed Abdul Bari, Shahanawaj Ahamad, Mohammed Rahmat Ali,” Smartphone Security and Protection Practices”, International Journal of Engineering and Applied Computer Science (IJEACS) ; ISBN: 9798799755577 Volume: 03, Issue: 01, December 2021
27. Shahanawaj Ahamad, Mohammed Abdul Bari, Big Data Processing Model for Smart City Design: A Systematic Review “, VOL 2021: ISSUE 08 IS SN : 0011-9342 ;Design Engineering (Toronto) Elsevier SCI Oct
28. Mohammed Abdul Bari, Shahanawaj Ahamad, Mohammed Rahmat Ali,” Smartphone Security and Protection Practices”, International Journal of Engineering and Applied Computer Science (IJEACS) ; ISBN: 9798799755577 Volume: 03, Issue: 01, December 2021 (International Journal,U K) Pages 1-6
29. S. Abney, "Statistical methods and linguistics" in The Balancing Act: Combining Symbolic and Statistical Approaches to Language, Cambridge, MA, USA, 1996.
30. C. Manning and H. Schutze, Foundations of Statistical Natural Language Processing, Cambridge, MA, USA:MIT Press, 1999.
31. Dr. M.A.Bari, ”EffectiveIDS To Mitigate The Packet Dropping Nodes From Manet “, JACE, Vol -6,Issue -6,June 2019
32. M.A.Bari & Shahanawaj Ahamad,” Process of Reverse Engineering of Enterprise InformationSystem Architecture” in International Journal of Computer Science Issues (IJCSI), Vol 8, Issue 5, ISSN: 1694-0814, pp:359-365,Mahebourg ,Republic of Mauritius , September 2011
33. M.A.Bari & Shahanawaj Ahamad, “Code Cloning: The Analysis, Detection and Removal”, in International Journal of Computer Applications(IJCA),ISSN:0975-887, ISBN:978-93-80749-18-3,Vol:20,No:7,pp:34-38,NewYork,U.S.A.,April 2011
34.

35. Ijteba Sultana, Mohd Abdul Bari and Sanjay," Impact of Intermediate Bottleneck Nodes on the QoS Provision in Wireless Infrastructure less Networks", Journal of Physics: Conference Series, Conf. Ser. 1998 012029 , CONSILIO Aug 2021
36. "Direction-based text interpretation as an information access refinement" in Text-Based Intelligent Systems: Current Research and Practice in Information Extraction and Retrieval, Berkeley, CA, USA:Lawrence Erlbaum Associates, pp. 257-274, 1992.
37. V. Hatzivassiloglou and K. McKeown, "Predicting the semantic orientation of adjectives", *Proc. 35th Annu. Meeting Assoc. Comput. Linguistics 8th Conf. Eur. Chapter Assoc. Comput. Linguistics*, 1997.
38. R. Kruse, D. Nauck and C. Borgelt, "Data mining with fuzzy methods: Status and perspectives", *Proc. 7th Eur. Congr. Intell. Techn. Soft Comput. (EUFIT)*, 1999.
39. A. Esuli and F. Sebastiani, "SentiWordNet: A publicly available lexical resource for opinion mining", *Proc. 5th Conf. Lang. Resour. Eval. (LREC)*, 2006.
40. E. Cambria and A. Hussain, Sentic Computing Techniques Tools and Applications, New York, NY, USA:Springer, 2012.
41. A. Kumar and T. M. Sebastian, "Sentiment analysis: A perspective on its past present and future", *Int. J. Intell. Syst. Appl.*, vol. 4, no. 10, pp. 1-14, Sep. 2012.
42. B. Pang, L. Lee and S. Vaithyanathan, "Thumbs up? Sentiment classification using machine learning techniques", *Proc. Conf. Empirical Methods Natural Lang. Process. (EMNLP)*, 2002.
43. P. Turney, "Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews", *Proc. 40th Annu. Meeting Assoc. Comput. Linguistics (ACL)*, 2002.
44. C. Banea, E. Mihalcea and J. Wiebe, "A bootstrapping method for building subjectivity lexicons for languages with scarce resources", *Proc. 6th Int. Conf. Lang. Resour. Eval. (LREC)*, 2008.
45. M. K. Dalal and M. A. Zaveri, "Semisupervised learning based opinion summarization and classification for online product reviews", *Appl. Comput. Intell. Soft Comput.*, vol. 2013, pp. 1-8, Jan. 2013.
46. B. Lu and B. K. Tsou, "Combining a large sentiment lexicon and machine learning for subjectivity classification", *Proc. Int. Conf. Mach. Learn. Cybern.*, Jul. 2010.
47. N. C. Dang, M. N. Moreno-Garcia and F. D. L. Prieta, "Sentiment analysis based on deep learning: A comparative study", *Electron. J.*, vol. 9, no. 483, pp. 1-29, 2020.
48. T. Mikolov, K. Chen, G. Corrado and J. Dean, "Efficient estimation of word representations in vector space", *Proc. Int. Conf. Learn. Represent.*, 2013.
49. J. Devlin, M. Chang, K. Lee and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding", *Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics*, 2019.
50. A. Giachanou and F. Crestani, "Like it or not: A survey of Twitter sentiment analysis methods", *ACM Comput. Surveys*, vol. 49, no. 2, pp. 28-41, 2016.
51. M. Thelwall, K. Buckley, G. Paltoglou, D. Cai and A. Kappas, "Sentiment strength detection in short informal text", *J. Amer. Soc. Inf. Sci. Technol.*, vol. 61, no. 12, pp. 2544-2558, Dec. 2010.
52. S. Loria, TextBlob: Simplified Text Processing, Mar. 2020, [online]


ISSN: 2456-4265



**DOI: https://doi-ds.org/doilink/09.2023-61724673**

53. C. Hutto and E. Gilbert, "VADER: A parsimonious rule-based model for sentiment analysis of social media text", *Proc. 8th Int. Conf. Weblogs Social Media (ICWSM)*, 2014.
54. Y. W. Teh, M. I. Jordan, M. J. Beal and D. M. Blei, "Sharing clusters among related groups: Hierarchical Dirichlet processes", *Proc. 17th Int. Conf. Neural Inf. Process. Syst.*, 2004.
55. A. Wilson and P. Chew, "Term weighting schemes for latent Dirichlet allocation", *Proc. Annu. Conf. North Amer. Chapter Assoc. Comput. Linguistics*, 2010.
56. J. Hansen, "Inside latent Dirichlet allocation: An empirical exploration", *Knowl. Inf. Syst.*, pp. 1-21, 2016.
57. Q. Mei, X. Shen and C. Zhai, "Automatic labeling of multinomial topic models", *Proc. 13th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining (KDD)*, 2007.
58. *Twitter US Airline Sentiment*, Feb. 2015.
59. A. Go, R. Bhayani and L. Huang, "Twitter sentiment classification using distant supervision", 2009.
60. H. Kwak, C. Lee, H. Park and S. Moon, "What is Twitter a social network or a news media?", *Proc. 19th Int. Conf. World Wide Web (WWW)*, 2010.
61. *List of Emoticons*, Apr. 2021, [online] Available: https://en.wikipedia.org/wiki/List_of_emoticons.
62. R. Botchway, A. Jibril, Z. Oplatkova and M. Chovancova, "Deductions from a Sub-Saharan African Bank's Tweets: A sentiment analysis approach", *Cogent Econ. Finance*, vol. 8, no. 1, pp. 1-19, 2020.